AI-Driven Early Warning Systems for Extreme Weather Protection of Electrical Grids: A Review

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ABSTRACT
Extreme weather conditions including floods, cyclones, lightning strikes, heat waves, fires, and storms continue to cause damage to modern electrical power systems through damage to transmission lines, substation equipment, transformer equipment, and communication equipment. Traditional protective equipment is reactive in nature when faults occur resulting in extended duration outage periods and financial loss. Thus, the use of Intelligent Early Warning Systems (I-EWS) has been deemed critical to increasing the overall resilience of power systems. A complete literature survey of weather hazard early warning techniques for power system protection was conducted. The survey included traditional forecasting techniques along with machine learning, deep learning, hybrid artificial intelligence systems, and Internet of Things (IoT)-enabled smart grid architecture. Articles from ScienceDirect, Springer, IEEE Xplore, Scopus, Web of Science, and Google Scholar were reviewed systematically using PRISMA-based screening methodologies. In contrast to prior reviews which emphasized individual weather hazards or specific predictive techniques, this study provided an integrated assessment of multiple hazards and their corresponding predictive techniques. Prior studies' predictive methods were categorized as statistical models, machine learning models, deep learning models, and hybrid models; further comparisons between each model type were made using criteria related to prediction accuracy, adaptability to changing conditions, processing time requirements/computational complexity, and technical difficulties associated with implementation. The authors highlighted that AI-based predictive models greatly enhance fault detection/prediction capabilities and increase the dependability/reliability of the power system while also noting several limitations in their current application including lack of real-time capability in deployments, lack of transparency/explainability in predictions, high rates of false alarm generation, cyber security vulnerabilities and lack of consideration for developing economies. Ultimately the authors identified key knowledge gaps in the field of AI-based I-EWS development and proposed a future framework incorporating AI-based predictive models combined with IoT devices and sensors, cloud computing resources, remote sensing technology and advanced smart grid equipment to provide support for both climate resilient power systems and intelligent grid protection.

Keywords: Early Warning System (EWS), Weather Hazards, Smart Power Systems, Climate Resilience, Machine Learning, Deep Learning, Quantum LSTM, Multi-Hazard Prediction, Smart Grid Protection, Outage Forecasting, Extreme Weather Events, IoT-Based Monitoring, Predictive Analytics, Adaptive Grid Protection, Power System Resilience.
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1. INTRODUCTION

The number and severity of extreme weather events have drastically increased since the beginning of the last decade primarily due to climate change and the increasingly unstable nature of our environment [1]. Modern electric utilities are very susceptible to these types of weather disasters because they operate over a wide geographic area and remain constantly exposed to the elements.

Weather related damages to electrical infrastructure include but are not limited to; wind (cyclones), flooding, lightning, heat waves, hurricanes, snow storms, wildfires and high precipitation rates can all affect transmission lines, substations, transformers, communication equipment and distribution systems [2] . These weather related failures can lead to significant disruptions in service by utility companies that can be devastating to society as well as damaging economically. Power is recognized as a vital part of infrastructure for this reason, hospitals, public transportation, manufacturing facilities, communication systems, banks, municipal water treatment plants, military operations and smart cities require continuous and reliable electrical power [3]. Short-term or even temporary loss of power can create major social and economic impacts. A study based on recent energy studies worldwide found that approximately 70% of all large scale power outages were attributed to weather related events [4]. For these reasons, protecting modern electrical networks from the effects of extreme weather conditions has become a major concern among researchers. Weather-related emergencies have caused numerous large-scale failures to existing electrical infrastructure. One example of such an event was hurricane Sandy which resulted in major power outages throughout the eastern seaboard of the USA and caused extensive damage to much of its' transmission infrastructure [5]. Another example is the February 2021 Texas Winter Storm event that caused a catastrophic failure of the state's electric grid due to extremely low temperatures and the resulting grid instability [6]. Cyclone Fani in May 2019 severely impacted the electrical infrastructure of Odisha and led to long duration outages in several areas of the region [7]. Flooding and lightning have also caused damage to substation and transformer equipment in various developing countries whose electrical grids lack sophisticated monitoring and protective capabilities. Figure 1 illustrates some examples of common extreme weather events impacting electrical power generation and delivery.

Figure 1. Major Weather Hazards Affecting Power Systems

Traditional power system protection approaches primarily operate reactively. The conventional relay, circuit breaker and fault isolation systems all react after faults occur in the power delivery network. While these protective measures are essential for maintaining grid reliability; however, they cannot anticipate impending threats nor can they implement preventative countermeasures prior to physical damage occurring. As a result, utility personnel experience difficulty when attempting to minimize outage durations and protect important equipment during extreme weather events. Due to this limitation, researchers have been focusing on developing Early Warning Systems (EWS) that will enable both the detection of impending hazards prior to their occurrence and provide timely notifications for the implementation of preventative countermeasures [13]. An early warning system is an intelligent predictive framework that is capable of detecting and predicting possible future hazards. Additionally, it provides timely warnings to take preventative countermeasures prior to the occurrence of the event [16]. For power systems, EWS's can assist utilities by enabling them to forecast weather-related risks, identify areas of vulnerability in the infrastructure, reduce outage restoration times, and enhance the overall effectiveness of their operational plans. This type of system enables utilities to plan for preventative maintenance activities, load redirections, dynamic switching, and emergency response planning prior to faults occurring.

Recent studies indicate that modern EWS frameworks combine numerous technologies including Artificial Intelligence (AI), Machine Learning (ml), Deep Learning (dl), Internet of Things (IoT), cloud computing, Geographic Information Systems (gis), satellite communications, remote sensing and advanced smart grid monitoring systems [10]. Historically utilized data sources include weather stations/sensors, phasor measurement units (pmu), smart meters, satellite imagery and historical outage record databases. A diagram showing the typical structure of intelligent EWS's for power network protection is provided in Figure 2.

Machine Learning algorithms such as Random Forest, support vector machines (SVM), decision trees, K-Nearest Neighbor (KNN) and XGBoost were found to be effective in various studies concerning weather forecasting and outage predictions [8]. These ml techniques utilize extensive amounts of past weather and operating data to establish patterns of failure in the distribution system. Also, dl algorithms such as Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN) and long short term memory (LSTM) networks are being utilized due to their enhanced capabilities to model non-linear relationships within complex weather phenomena and make accurate predictions in real-time [12].

Hybrid intelligent systems have been studied using combinations of ai and IoT/cloud computing technologies. IoT enabled devices collect and transmit real-time data regarding environmental/physical condition of the electric distribution system [10]. Cloud-based platforms store massive amounts of collected data while allowing for rapid processing. Remote sensing/GIS technology enhances the ability to visualize and assess spatially related hazards/risk assessments. Advanced communication protocols within smart grids improve the capacity of the adaptive/self-healing characteristics of today's electrical grids [14].

Despite recent advancements in technology there are still several challenges present in the current state of research. Most existing EWS's address only one particular type of hazardous weather phenomenon i.e., flooding/windstorm. Real-world electric power distribution systems are subject to a variety of simultaneous hazardous weather conditions. Currently available models exhibit excessive computational complexities, generate false alarms, possess limited explainability and lack interoperability among disparate monitoring platforms [15]. Furthermore, most ai based models require substantial data sets and expensive computational resources, limiting practical application in underdeveloped countries.

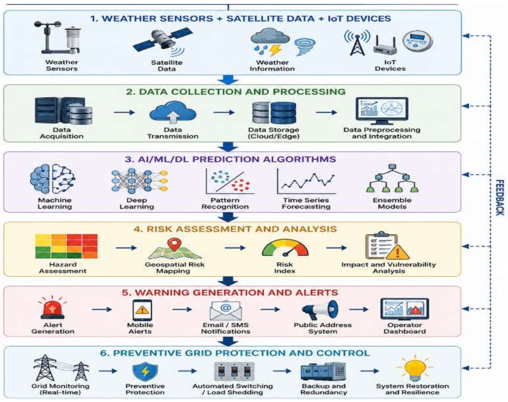

Figure 2. General Architecture of Weather Hazard Early Warning System

An additional critical issue is the lack of intelligent warning frameworks specific to the power grid. The majority of current disaster management systems have been created for general environmental monitoring purposes as opposed to protecting electrical infrastructure. Therefore, such systems do not possess the ability to generate adaptive operating decisions concerning transmission and distribution networks. Moreover, very little published research has been conducted regarding the development of early warning systems for developing countries whose electrical infrastructure is particularly susceptible to climate-related disasters because of older electrical equipment, high population densities, and less disaster preparedness capacity.

Therefore, one of the main reasons for conducting this research is the pressing need to create climate resilient electric power systems capable of anticipating and mitigating weather-related failure events. Reactive protective systems currently in use are incapable of addressing today's climate driven threats. An imperative exists for the creation of intelligent and adaptive early warning systems that will enable predictive maintenance, real time hazard forecasting and proactive operational decision making. The combination of Artificial Intelligence (AI), Internet of Things (IoT), Cloud Computing and Smart Grid technologies may significantly enhance both the resilience of the grid and its ability to prepare for potential disasters.

The primary concern addressed by this document is the absence of an integrative review of various types of weather hazard early warning methodologies that are specific to the protection of power systems. Previous reviews of literature have focused primarily on single technologies or individual hazards. Very few studies exist which compare and contrast traditional methodologies with Machine Learning approaches, Deep Learning frameworks, Hybrid Intelligent Systems and other methodologies within a common context. This paper therefore intends to present a comprehensive and systemic overview of all recent developments relating to weather hazard early warning systems that support resilient electricity infrastructure. The overall methodological approach employed in this review is based upon the Systematic Literature Review (SLR) and PRISMA framework. Articles pertaining to research related to weather hazards, smart grids, artificial intelligence, machine learning, deep learning, and power system resilience were obtained from IEEE Xplore, ScienceDirect, Springer, Scopus, Web of Science, and Google Scholar databases employing predetermined keyword combinations associated with weather hazards, smart grids, artificial intelligence, machine learning, deep learning and power system resilience. Papers that satisfied the inclusion criteria were reviewed with respect to methodology, prediction performance, type of hazard predicted, computational requirements/complexity, real time capabilities, and impediments to successful implementation. Figure 3 illustrates the overall review methodology employed in this effort.

This paper makes significant contributions. First, it represents a thorough review of traditional weather forecasting and protection methods utilized in electric power systems. Second, it conducts a systemic analysis of Machine Learning and Deep Learning methodologies that have been applied to predict weather hazards and estimate outages. Third, Hybrid Intelligent Systems which incorporate IoT, Cloud Computing, Geographic Information Systems (GIS), and Smart Grid Technologies are evaluated in detail. Fourth, the major gaps in research and barriers to implementing intelligent multi-hazard early warning systems are described. Fifth, possible directions for future research regarding the development of advanced intelligent multi-hazard early warning systems are outlined.

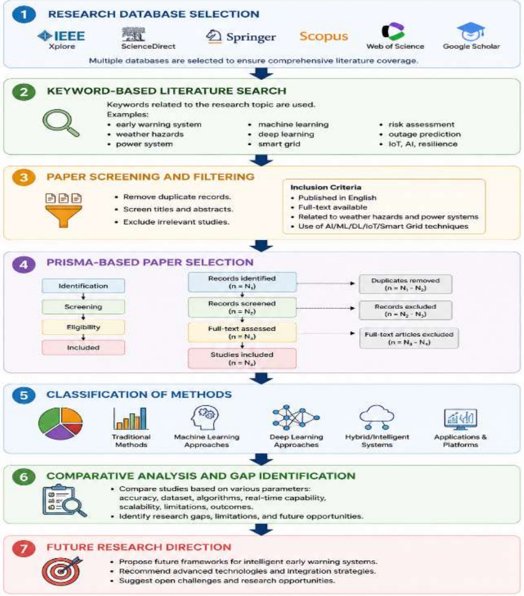

Figure 3. General Methodology of the Systematic Review

The remainder of this document is arranged in the following manner. Section II will explain how to use a systematic approach and discuss a PRISMA-structured method of selecting articles. In section III, we will describe typical weather-related hazards that impact electric power delivery systems. Section IV will be an overview of various forms of early warnings using machine learning. Section V will cover two types of smart methods (deep learning) and (hybrid intelligent frameworks). Section VI will detail comparisons between the different methods described above, and identify gaps within existing research. Section VII will provide additional opportunities for future research and propose the intelligent frameworks previously discussed. Section VIII will summarize this paper.

2. BACKGROUND OF EARLY WARNING SYSTEMS (EWS)

A variety of intelligent monitoring and prediction systems known as Early Warning Systems (EWS) will be able to recognize impending hazards prior to their occurrence and send timely warnings so that preventative measures may be taken by the end-users [16]. EWS are an important component of disaster management, infrastructure protection, environmental monitoring and critical power system operations. An EWS' most basic goal is to limit the amount of damage resulting from a hazardous event; lower operational risk; increase the ability to respond to an emergency situation quickly; and improve the overall resilience of a system during hazardous events [14].

In the past, traditional early warning systems were primarily based on natural disaster management such as flood detection; cyclone detection; earthquake detection; drought detection; storm detection [18] etc. A lot of these systems relied upon weather observation data; statistical forecasting techniques; thresholds-based alarms; and manual decision making processes.

Traditional warning systems did contribute to improving the preparedness for disaster scenarios to a certain degree but had low levels of prediction accuracy; were slow to react to a threat; and were not very adaptable in real-time. Due to the increased rate at which climate related disaster events occur, these types of systems have been deemed insufficient for providing adequate protection for today's smart infrastructure systems.

The concept of EWS has experienced a dramatic expansion in recent years due to technological advances in artificial intelligence (AI); machine learning (ML); internet of things (IoT); cloud computing; remote sensing and smart grid technologies [19]. The new EWS frameworks utilize diverse data streams such as weather sensors; satellite imagery; radar systems; smart meters; phasor measurement units (PMUs); and historical outage database information [21]. The framework continues to collect and analyze real-time environmental and operational information and uses predictive algorithms to identify potential hazards and warn users.

The general architecture of an EWS typically contains four main sub-components: risk knowledge; monitoring & forecasting; warning dissemination; and response capability [18]. Risk knowledge identifies hazards and assesses vulnerabilities. The monitoring and forecasting module monitors environmental conditions in real-time utilizing predictive algorithms. Warning dissemination provides notifications or alerts to the appropriate authorities (utilities, operators, etc.) when a hazard exists. Response capability involves taking corrective actions (load redistribution; emergency shutdown; dynamic switching; restoration planning; etc.) when a hazard is identified [16].

Electrical power systems represent another important application area for intelligent EWS. Weather-related events cause frequent disruptions to electrical infrastructure reliability. Weather-related failures can occur at numerous locations throughout a power system such as transmission tower failure; transformer failure; substation failure; overhead line failure; underground cable failure; communication network failure. Because contemporary electrical grids are increasingly interconnected and more complex, weather induced failures can easily propagate to other locations and result in widespread cascading outages [27]. As a result, predictive warning mechanisms are becoming more necessary to ensure grid stability and maintain continuous operation.

Machine learning (ML) and deep learning (DL) have enhanced the capabilities of present day EWS frameworks. Many popular ML algorithms utilized for outage predictions, risk classifications, fault forecasts include random forest, decision tree, SVM, and XGboost [8]. DL models including ANN, CNN, RNN, and LSTM networks demonstrate superior performance for non-linear weather forecasting tasks and time series analyses. In comparison with traditional statistical methodologies, intelligent approaches offer higher forecasting precision. Smart sensors enabled through IoT also play an important role in the development of the latest EWS architectures. These devices continue to monitor environmental parameters such as temperature, humidity, wind speed, rain fall intensity, lightening activity, and transformer loading conditions [10]. Cloud-based platforms also support large-scale data storage, distributed processing, and real-time analytical functions. Geographical Information System (GIS) technologies combined with remote-sensing technologies enable spatial hazard assessments and improve geographically based emergency planning [23].

Although significant advancements have occurred in the EWS space, additional challenges remain in both researching and implementing current EWS solutions. A majority of the currently available EWS systems focus solely on predicting individual hazards versus providing integrated multi-hazard forecasting services [30]. In terms of large scale utility implementations, many existing systems experience problems with real-time deployment complexities; cyber security threats; high false alarm rates; interoperability limitations; and high computation costs. Additionally, many AI-based systems act as black box models lacking interpretability which can negatively impact operator confidence when utilizing these tools for critical decision-making activities [25]. Furthermore, there remains a lack of grid specific intelligent warning systems for developing countries. Most advanced EWS frameworks are being implemented within highly digitized smart-grids having robust communication infrastructures [24]. Conversely, developing regions often experience outdated electrical infrastructure; limited deployment of smart sensors; inadequate monitoring capabilities; and limited preparedness for disaster responses. There is therefore a strong demand for adaptive scalable cost effective EWS frameworks tailored for climate-resilient power systems.

Early Warning Systems have progressed from simple disaster alerting mechanisms into sophisticated predictive frameworks enabling protection of modern smart-grid infrastructure along with enhancing resilient infrastructure management capabilities. The integration of AI, IoT, cloud computing and advanced weather analytics has provided novel opportunities for predictive hazard mitigation/adaptive grid operation [20]. As a consequence, EWS represents an emerging research area for next generation climate-resilient power systems/intelligent disaster management.

3. WEATHER HAZARDS IN POWER SYSTEMS

Climate and weather have dramatically changed the nature of power systems over the last few decades. Because much of the infrastructure for transmitting and distributing power is spread over long distances, these systems are very susceptible to extreme weather events such as floods, droughts, wildfires, and storms. This vulnerability has the potential to lead to disruptions in the reliability, stability, security, and performance of power delivery systems. For example, extreme weather can destroy transmission towers, transformers, substations, communications systems, underground cabling, and distribution feeders; it can also result in widespread blackouts and substantial financial loss. Of all the extreme weather events that threaten power systems, windstorms (e.g., hurricanes) and cyclones are generally the most damaging. Windstorms can bring down transmission towers and damage overhead wires through both direct force and flying debris. Additionally, they can bring heavy rain causing additional problems for substation and underground wiring infrastructure. As a result of their potential to disrupt an entire grid, large-scale storm events often result in cascading failures throughout an interconnected grid. This results in greater restoration difficulty and longer durations of outages [29].

In addition to windstorm/cyclone type of natural disaster, floods can also be extremely detrimental to electric infrastructure. Floodwaters can enter into substations, transformers, switchgear equipment, underground cabling and other components creating electrical shock hazards when energized. Moisture related issues including corona discharges, electrical arcing, corrosion and equipment malfunction can occur. Floodwaters can make it difficult or impossible to access underground cabling systems for maintenance/repair purposes. Many studies have indicated that there has been a significant increase in flood related outages within urban areas resulting primarily from inadequate drainage systems and rapid urbanization [32].

High temperature (heatwave) related issues can also negatively affect the operation of modern power systems. Heatwaves cause an increase in peak summer load due to the extensive use of cooling devices; at the same time they decrease the efficiency of the transmission of electricity. When the temperature exceeds normal levels, transformers and overhead wire conductors begin to overheat as a result of excessive thermal stresses. High temperatures cause overhead wire conductors to sag thus increasing the likelihood of fault occurrence and safety violation. If a prolonged heat wave occurs, it will likely shorten the life expectancy of a transformer and cause problems with the stability of a substation [34].

Faults caused by lightning are among the most frequent occurrences in the transmission/distribution systems. A lightning strike can produce voltage surges that damage insulated systems, relays, transformers, circuit breakers, communication equipment etc. Overhead transmission lines that operate in mountainous/hilly terrain and/or those that operate in wet climates tend to experience lightning induced faults more frequently than do those operating in non-mountainous/flat terrain and dry climates. In addition to producing faults, repeated lightning events can increase maintenance expenditures and degrade overall reliability of a grid. While surge protectors and grounding systems are typically utilized for protection against lightning strikes, severe lightning events continue to pose challenges to utility companies' ability to maintain safe grid operations [44].

Wildfires have become a growing concern for electrical engineers in recent years. The combination of hot temperatures, dry plant material and strong winds creates a higher chance for wildland fire to start along transmission corridors [37]. Fires can physically damage transmission lines, substations, poles and communication equipment. The smoke particulate matter and heat produced by fires can also cause flashovers and insulation breakdowns in high voltage systems. On occasion electrical equipment itself can ignite wildfires either by way of a conductor fault or equipment failure [37].

Storms/rainfalls severely impact underground cable systems and low lying substations. Heavy rainfall can erode the insulation on underground cable causing faults to develop [38]. Water accumulating around electrical equipment raises the risks for shorts-circuits and ground faults. During urban smart grid deployments heavy rainfall events can create simultaneous failures in multiple types of infrastructures (transportation systems, communication networks, electric distribution systems etc.) [39].

Winter storms and ice formation are primary concerns in cold climate locations. Ice forming on conductors increases mechanically loads on overhead transmission lines and towers [40]. Excessive amounts of ice accumulation can cause breakage of conductors and/or damage to insulators as well as collapse support structures. Winter storms can limit maintenance personnel's ability to work on the line making restoration efforts slower. Also freezing temperatures can adversely affect transformer oil properties and batteries used in substations/back-up power sources [41].

While weather events can damage physical infrastructure associated with power delivery systems, they also present operational/economic challenges for utility organizations. Severe weather events can raise the cost of restoration, lower grid reliability and stop production in industries dependent upon electrical energy; they can also impair public safety [42]. Due to the connectivity between today's smart-grids and the fact that localized weather event effects can travel quickly across geographically dispersed networks, predicting hazardous weather event(s) is now more important than ever before [43]. Researches have recently concentrated efforts toward improving weather-related hazard predictions utilizing various AI-based tools (e.g., artificial intelligence (AI), machine learning (ML), deep learning (DL), internet-of-things (IoT) sensors and remote-sensing technologies). Predictive capabilities based on weather forecasting models assist utility organizations to provide advance warning of impending hazardous weather events thereby enabling them to pre-determine possible outage locations, schedule/preventative maintenance schedules and adaptively manage their operations [7]; however most current predictive models have limitations in terms of their capacity to integrate multiple hazardous weather events simultaneously into a single model; their propensity to create false alarms; their lack of transparency/explainability; and their computational complexity [15].

Another growing problem for utility organizations involves uncertainty associated with climate change. Due to changes associated with climate change, weather pattern behaviors are changing dynamically and are becoming increasingly difficult to predict statistically [1]. Much of the infrastructure developed for power delivery in many developing nations was never intended to endure modern climate extremes. Consequently, utility organizations require advanced climate-resilience monitoring/protection methodologies capable of functioning effectively under a variety of environmental conditions [43].

Weather hazards pose a significant threat to modern electric power delivery systems. Climate driven catastrophes are occurring with increasing frequency therefore it is necessary to develop intelligent Early Warning Systems with predictive risk assessment abilities for adaptive protection functions for grids. An understanding of how individual weather-related hazards impact electric infrastructure is essential for planning resilient/reliable/sustainable power delivery networks for the future [2].

4. EXISTING LITERATURE SURVEY

A systematic review of research papers post-2018 indicates that Machine Learning (ML)-based frameworks are increasingly being used to enhance both weather hazard prediction and power system resilience. These include applications such as outage forecasting, storm prediction, infrastructure vulnerability assessments, and predictive/preventive operation of the electric grid. This paper reviews current literature focused on outage prediction in the context of severe weather events.

Prieto-Godino et al. [58] proposed a deep learning framework for detecting weather related outages in the electric grid through the application of ensembling techniques. The authors reported improved accuracy in identifying extreme outage events at the expense of lower false alarm rates. However, they noted that the framework would require extensive historical outage data for training. Ghasemkhani et al. [59] also developed an XGBoost machine learning framework for predicting the duration of power outages in utility networks. They reported a prediction accuracy of approximately 98.43 percent when applying their model to real world outage data. The authors concluded that the success of this approach was heavily dependent upon the quality of the feature engineering and pre-processing of the input data. Fatima et al. [60] proposed an ensemble machine learning framework for predicting hurricane induced outages using both weather and grid data. The authors concluded that ensemble approaches produced better outage forecasts than traditional methods. However, they noted that the level of explainability of the system decreased as the number and complexity of weather conditions increased.

AlHaddad et al. [61] proposed an ensemble learning based outage prediction model for sustainable energy grids subjected to hurricane force winds. The authors demonstrated how this type of modeling can be useful for developing and implementing resilient plans for mitigating damage caused by hurricanes. However, they acknowledged that increased computational complexity will limit its applicability to larger scale smart grid deployments. Lee et al. [62] proposed a machine learning based predictive framework for predicting outages due to extreme weather events. The authors utilized outage data from the Electric Grid Assessment and Location Enhancement Initiative (EAGLE-I) and the National Weather Service to train and validate their model. Their results indicated that they were able to improve the ability to predict outages at a statewide level. However, they identified several limitations including inconsistencies in the data and difficulties with handling missing values. Lee et al. [63] proposed a machine learning based outage prediction model utilizing publicly available weather data and utility outage records. The authors demonstrated that these types of models can provide valuable proactive support for outage management. However, they noted that their model did not utilize real time adaptive learning capabilities.

Dolgun et al. [64] proposed a probabilistic machine learning framework incorporating Random Forest and Support Vector Machine (SVM) algorithms for predicting outages caused by adverse weather conditions. The authors reported nearly 93 percent accuracy when applying the Random Forest algorithm. However, they noted that this type of framework requires continuous retraining in order to adapt to changes in climate. Azizi et al. [65] proposed a generative machine learning framework for enhancing predictions of outages resulting from rare extreme weather conditions. The authors demonstrated improvements in generating synthetic data for low frequency outage events. However, they noted that this framework requires high levels of computing resources and involves complex training procedures. Ajeigbe et al. [66] proposed three different machine learning models for detecting outages in distribution networks resulting from faults. The three models included Random Forest, Logistic Regression, and k-nearest neighbor (KNN). The authors demonstrated improved disturbance classification and faster restoration speeds when comparing these models to previous approaches. However, they noted that these models had reduced accuracy in noisy sensor environments.

Biswas et al. [67] developed a learning based outage prediction framework combining weather, infrastructure, and socio economic data. The authors utilized long short term memory (LSTM) assisted machine learning models to demonstrate improved accuracy for low probability outage events. However, they noted that there is currently little understanding of how well this type of model may be interpretable. Wang et al. [68] proposed a deep learning assisted weather outage prediction framework using socioeconomic and infrastructure data. The authors demonstrated improved hourly outage probability prediction capability. However, they noted that the development of this type of model requires extensive amounts of collected data which then need to be processed into usable formats. Arora et al. [69] proposed both probabilistic and machine learning approaches for designing uncertainty aware outage prediction systems. The authors demonstrated improved reliability of outage estimates when considering uncertainties in weather conditions. However, they stated that one area of ongoing concern is bounding the outage prediction. Kezunovic et al. [70] proposed a big-data driven machine learning framework for predicting outages using over sixty different environmental and operational parameters. The authors demonstrated enhanced proactive outage mitigation capability. However, they stated that it is highly likely that the complexity of integrating multiple heterogeneous datasets will increase significantly.

Zhu et al. [71] proposed a hybrid machine learning framework using satellite nighttime light data and weather information to reconstruct hurricane induced outages. The authors demonstrated superior performance when applying XGBoost and Random Forest models versus CNNs. However, they noted that cloud contamination of satellite images has negative impacts on consistency of the predictions. Zhang et al. [72] provided a review of potential vulnerabilities of machine learning (ML) based smart grid applications along with highlighting potential cybersecurity threats associated with AI driven outage prediction systems. In particular, they emphasized challenges associated with defending against adversarial attacks on intelligent grid infrastructure. However, they noted that defensive technologies remain relatively immature. Ardito et al. [73] examined the effects of adversarial attacks on ML based smart grid fault prediction systems. The authors demonstrated that many outage prediction frameworks utilizing neural networks are vulnerable to malicious perturbations introduced via adversarial attacks. However, they acknowledged that very few practical defences exist today.

Overall, collective work from recent studies clearly shows that ML techniques offer substantial enhancements to outage predictions, hazard classifications, and resilience planning in modern smart grids. Nonetheless, most of the frameworks described above continue to have issues with scalability; lack in Explainable Artificial Intelligence (XAI); have limitations regarding multi-hazard predictions; are susceptible to cyber security threats; and depend heavily on having high quality datasets available to them.

5. COMPARATIVE ANALYSIS

Table 1 presents the comparative analysis of recent Machine Learning-based weather hazard prediction and outage forecasting techniques proposed in the literature. The comparison is performed based on methodology, application area, performance, advantages, and existing limitations.

Table 1. Comparative Analysis of Existing ML-Based Weather Hazard Prediction Systems

Ref.	Author	Method Used	Application Area	Major Result	Limitation
[59]	Ghasemkhani et al.	XGBoost + MRMR	Outage duration prediction	Achieved 98.43% accuracy	Requires extensive feature engineering
[60]	Fatima et al.	Ensemble ML Models	Hurricane outage forecasting	Improved outage prediction reliability	Limited explainability
[61]	AlHaddad et al.	Ensemble Learning	Hurricane resilience planning	Better vulnerable component identification	High computational complexity
[62]	Lee et al.	ML Prediction Framework	Extreme weather outage prediction	Improved state-level outage forecasting	Missing-value handling issues
[63]	Lee et al.	ML + Utility Datasets	Proactive outage management	Effective outage prediction capability	Lack of adaptive learning
[64]	Dolgun et al.	Random Forest + SVM	Weather outage probability prediction	RF achieved nearly 93% accuracy	Requires continuous retraining
[65]	Azizi et al.	Generative ML Models	Rare weather outage prediction	Improved imbalance handling	High training complexity
[66]	Ajeigbe et al.	RF + Logistic Regression + KNN	Fault detection	Improved restoration speed	Sensitive to noisy data
[67]	Biswas et al.	LSTM-assist	Extreme-event outage	Better low-probability	Low interpretability

		ed ML	prediction	outage prediction	
[68]	Wang et al.	DL-assisted ML Framework	Hourly outage prediction	Improved outage probability estimation	Large data requirement
[69]	Arora et al.	Probabilistic ML	Uncertainty-aware outage prediction	Improved reliability estimation	Prediction bounds remain difficult
[70]	Kezunovic et al.	Big Data ML Framework	Smart grid outage forecasting	Improved proactive mitigation	High integration complexity
[71]	Zhu et al.	XGBoost + RF + Satellite Data	Hurricane outage reconstruction	Better reconstruction accuracy	Cloud contamination issue
[72]	Zhang et al.	ML Vulnerability Analysis	Smart grid cybersecurity	Identified adversarial vulnerabilities	Defensive mechanisms immature
[73]	Ardito et al.	Adversarial ML	Fault prediction security	Demonstrated attack vulnerability	Limited protection strategies
[64]	Dolgun et al.	Probabilistic ML	Customer outage notification	Reduced economic losses	Real deployment challenges
[58]	Prieto-Godino et al.	DL Ensemble Models	Large-scale outage prediction	Improved extreme-event detection	False alarms still present
[65]	Azizi et al.	Synthetic Data ML	Data imbalance handling	Better rare-event prediction	Computationally expensive
[67]	Biswas et al.	Hybrid ML + Infrastructure Data	Climate-event outage prediction	Better resilience estimation	Complex model tuning
[68]	Wang et al.	Socio-economic DL Models	Infrastructure-aware prediction	Improved temporal prediction	Extensive preprocessing required

A comparative analysis of Machine Learning methods reveals that predictive performance of weather hazard prediction and outage forecasting can be significantly improved when using Machine Learning approaches compared to traditional statistical models. Much recent research has focused on ensemble learning, probabilistic prediction, and hybrid AI frameworks to improve grid resiliency under extreme weather conditions. Studies showed high accuracy in outage forecasting applications by utilizing XGBoost, Random Forest and ensemble learning techniques [59] [61] [64]. Such methods are effective in processing heterogeneous data sources and supporting utility operator intelligent decision-making. Nevertheless, their success is highly dependent upon the quality of features selected and availability of historical data.

Deep Learning-assisted frameworks such as lstm and hybrid dl models also improves non-linear weather event modeling capability and temporal prediction capability [67] [68]. Such models perform well in dynamic climate scenarios and complex outage situations. However, they require large-scale computational resources and labelled datasets. Probabilistic ML methods provides uncertainty-aware outage prediction and resilience estimation capability [69]. Such frameworks allow utility operators to understand confidence levels associated with predicted outages. However, optimization within a predictive-bound remains a challenging problem for researchers.

Several studies have incorporated satellite imagery, GIS data, socio-economic information, and weather data to support multi-dimensional hazard assessment [68][71]. Such hybrid intelligent frameworks improve geographical risk assessment and infrastructure vulnerability analysis. Nevertheless, integration complexity and interoperability issues remain major challenges. Additionally, cybersecurity has emerged as an important concern for intelligent smart grid prediction systems. Recent studies have demonstrated that ml-based outage prediction frameworks are vulnerable to adversarial attacks and malicious data perturbations [72][73]. Currently available defence mechanisms remain immature and will continue to need further research attention.

Another important observation is that many existing frameworks focus only on single-hazard prediction such as hurricanes or storms. There is limited research available for integrated multi-hazard early warning systems capable of simultaneously addressing floods, lightning, heatwaves, cyclones, wildfire conditions. Furthermore, many studies lack real-time deployment capability and adaptive online learning mechanisms.

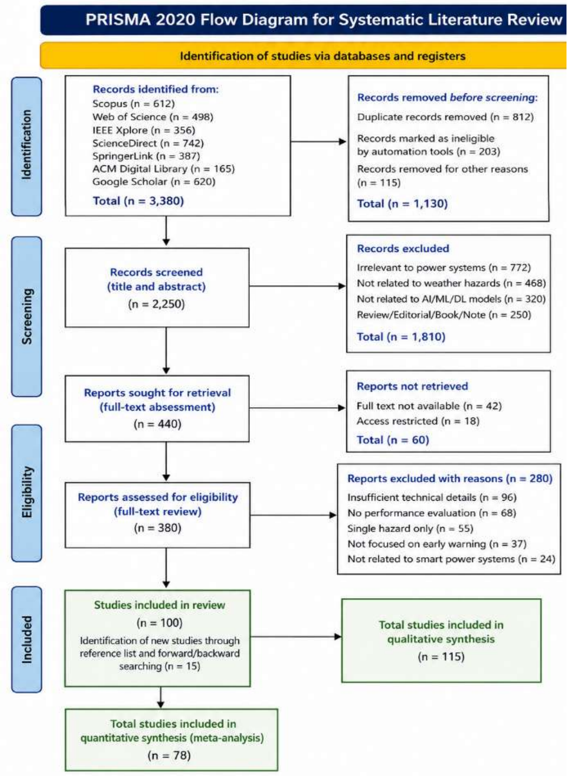

Figure 4. PRISMA 2020 Flow Diagram for Systematic Literature Review of AI-Based Weather Hazard Early Warning Systems in Smart Power Networks.

Figure 4 shows the methodology of this study based on a systematic literature review according to PRISMA 2020. It describes the full procedure of selecting the relevant papers through identifying, screening, assessing eligibility and finally including them. For collecting research papers, the authors used predefined search terms regarding weather hazards, smart grids, machine learning and early warning systems, in order to collect these from major science databases like IEEE Xplore, Scopus, ScienceDirect, Springer, and Web of Science.The application of the PRISMA methodology guaranteed an enhanced transparency compared to non-PRISMA methodologies, minimized the risk of biases in the selection of papers, and guaranteed the inclusion of research papers of high quality and relevance in the analysis.

In summary, the comparison demonstrates that recent outage prediction systems, which rely on machine learning methods have shown great performance enhancements in predicting outages accurately, assessing resilience and conducting preventive control actions. However, it can be concluded that future intelligent early warning systems should address explainable AI (XAI), real-time implementation, adaptive learning capabilities, cyber security protection, and scalable multi-hazard integration frameworks for building climate resilient smart power systems.

6. RESEARCH GAPS

Although important achievements have already been made in weather hazard predictions and power system resiliency research, several important research gaps remain open at present for the current early warning system (EWS) frameworks. Most studies conducted so far investigated single-hazard predictions such as hurricanes, floods, lightning, or heat-waves separately [59]-[71]. As however today's power systems face multiple simultaneous weather hazards, very few research activities deal with integrated multi-hazard prediction systems capable of dealing with multiple climate events in real time. An additional drawback is that most existing Machine Learning and Deep Learning approaches do not include an adaptive learning mechanism for adapting to changes in their environment. Many approaches rely on historic data sets and off-line training [60], [64]. Therefore, they cannot learn dynamically under rapidly changing environmental conditions and/or evolving climate pattern. Moreover, many AI-based prediction approaches are considered as "black box" approaches with little interpretability by operators; therefore, they are less trustworthy when being used for decision-making processes during critical grid management situations. Some research studies were able to achieve high accuracy values in laboratory settings. However, the practical realization of large scale deployments of these approaches remains restricted [61], [70]; reasons for this restriction may include high computational costs, necessary investments into expensive infrastructure components, and integration difficulties into utility environments. Further restrictions arise from heterogeneity among different types of communication protocols and data formats of weather sensors, IoT-devices, GIS-platforms and smart-grid-systems; thus resulting in inter-operability problems. Another challenge is concerned with cybersecurity aspects in intelligent EWS-frameworks. Several recent studies demonstrated that ML-based Smart Grid Systems can be attacked by adversaries and manipulated by malicious actors [72], [73]. However, there is currently no sufficient number of robust security-aware EWS architectures described in current literature.

Finally, there is limited research focused on developing countries where the number of climate-related grid failures increases dramatically; this increase is driven by aging infrastructures, fast growing urban areas, and the lack of disaster preparedness capabilities. Since most existing EWS-frameworks are designed for the highly digitalized smart grids typical for industrialized countries, there exists a strong demand for scalable, cost-effective, interpretable and climate-resilient EWS-intelligent systems for protecting today's power system against multi-hazard environmental conditions.

Proposed Quantum LSTM-Based Framework:

The increasingly frequent occurrence of extreme weather phenomena creates new challenges for today's modern Smart Power Systems. Many conventional machine learning (ML) and deep learning (DL) techniques have high computational complexities, poor adaptability, and therefore less precise weather forecast capabilities when applied under extremely variable climate conditions. To address these issues, we develop an intelligent early warning framework based on a quantum long short-term memory (Q-LSTM)-based multi-hazard weather prediction and robust smart power system protection. Quantum LSTM is a powerful hybrid computational method which combines the temporal learning capabilities of classical LSTM-based networks with the efficient parallel processing characteristics of quantum computers. As opposed to most other classical LSTMs, q-LSTM makes use of quantum states and quantum gate operations for efficiently handling very complex sequential weather data sets. Furthermore, our developed framework provides enhanced spatial-temporal weather forecasting abilities, improved adaptive learning capabilities, and higher precision multi-hazard predictions than state-of-the-art techniques for climate-resilient smart grids.

We will integrate various types of hardware including weather sensors, IoT devices, remote sensing satellites, phasor measurement units (PMUs), geographic information systems (GIS) and historical outage databases for real-time monitoring of environmental factors. We will collect a variety of data sets including temperature, humidity, rain fall intensity, wind speed, lightning strikes, transformer loads, vegetation density, and previous outage data. All of these diverse data sources will be communicated through a cloud-processed layer where we can perform all necessary pre-processing operations; i.e., remove noise from each data set, extract features, normalize values across each data set, and reduce the dimensions of the resulting data sets.

Next, we will send the pre-processed data sets to the Quantum LSTM Predictive Model. The Q-LSTM Model uses quantum-enhanced computational layers to learn the sequential patterns in each time series. The quantum nature of Q-LSTM allows it to analyze non-linear temporal dependencies among variables more quickly and accurately than other existing models. Additionally, since Q-LSTM uses quantum superposition to process multiple input values in parallel, it significantly decreases computational delays experienced by real-time hazard prediction.

Our developed Q-LSTM-based system will provide simultaneous multi-hazard predictions for cyclone storms, flooding due to storm surges or river overflows, lightning storms, heat waves, heavy rainfall events, forest fires/wildfires caused by droughts, and snow storms. Traditional machine learning-based approaches typically focus only on predicting one type of hazard at a time whereas our system will predict correlated environmental risks dynamically. The Q-LSTM Model will continually generate probabilistic estimates of the likelihood of specific weather-related hazards occurring along with corresponding indices of vulnerability of critical grid assets such as overhead transmission lines, substation equipment, transformers and underground cables. The output from the Q-LSTM Model is then passed onto the Intelligent Risk Assessment Module. Within this module, we categorize the severity level of potential hazardous events as either low risk, moderate risk, high risk or critical risk. The estimated risk levels are used by the Early Warning System to issue proactive warnings to utility operators. These warnings may include actions such as: preventive switching, adaptive load shifting, protective measures for transformers and related equipment, development of emergency restoration plans and strategies for controlled islanding in emergency situations as well as scheduling predictive maintenance tasks for potentially vulnerable equipment.

In addition to generating actionable intelligence for proactive grid management decisions, the proposed Q-LSTM-based framework incorporates explainable artificial intelligence (xai) mechanisms to enhance transparency and confidence of utility operators regarding how environmental parameters relate to predicted outages. By providing insight into the decision making process associated with xai explanations, utility operators can make better informed real-time decisions regarding the operation of their grids in emergency situations. Another key advantage of the proposed Q-LSTM-based framework is its ability to process large amounts of sequential weather data rapidly relative to traditional deep learning models. Our proposed framework offers enhanced prediction accuracy, faster forecasting times, greater adaptability and increased multi-hazard awareness concurrently. Finally, by integrating edge computing capabilities with cloud resources in our proposed framework, we offer scalable architecture suitable for near-real-time deployments in smart grid environments

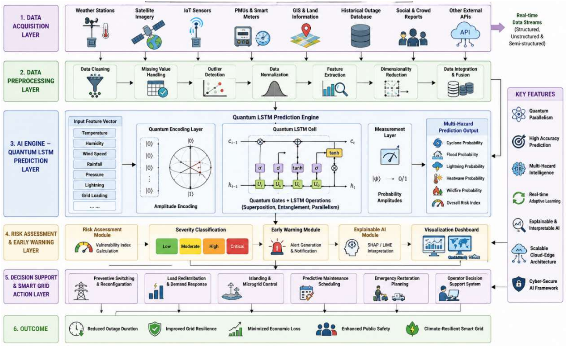

Figure 5. Proposed Quantum LSTM-Based Multi-Hazard Early Warning Architecture for Climate-Resilient Smart Power Systems.

The proposed Quantum LSTM-based early warning framework will provide an important contribution to the development of future climate-resilient power systems in four ways. It is capable of supporting a single platform that can forecast multiple hazards during variable and high-dynamic weather conditions. Additionally, it uses both deep-sequential-learning (using LSTMs) and Quantum Computing (as its primary method for predicting outages). Furthermore, by utilizing both Predictive Analytics and Smart Operational Control methods, it enables enhanced real-time adaptive Grid Protection capabilities. Finally, this proposed framework is establishing the foundational components necessary to develop future Self-Healing and AI driven Resilient Smart Grid Architectures. Overall, the proposed Q-LSTM architecture represents the next generation of Intelligent Weather Hazard Prediction Systems which are capable of enhancing Power System Resiliency, Reliability and Preventative Disasters Preparedness as well as Providing Enhanced Grid Protection Capabilities under Extreme Environmental Conditions.

6. CHALLENGES AND FUTURE SCOPE

The most significant problem with many smart grid technologies today is that they do not function well in the presence of missing or incorrect weather data. Many current weather monitoring systems use satellites, IoT devices, and utility company database systems which collect disparate and sometimes unreliable data. Often this data contains too much noise or is missing values altogether. Due to these inaccuracies it becomes difficult to predict the future performance of the electric grid. One other key concern is that our ability to forecast the future is becoming increasingly complex. Our climate is changing very quickly. It is difficult for many machine learning models to be able to predict how our climate will behave over time when there are so many variables involved. Many models are developed based on historical weather trends, but have difficulty predicting what will happen during unusual weather events. If a model cannot make reliable predictions, then it makes it difficult for utility companies to make decisions about how to manage their grid in real-time.

A third area of concern in smart grids is related to computation costs. As we develop more sophisticated artificial intelligence and deep learning techniques, we need powerful computers to run them. Unfortunately, few utilities around the world have access to this type of hardware. In fact, many small utilities in developing countries don't even have enough resources to deploy these types of systems. Therefore, while these models may be useful in providing better forecasts for certain areas, they may not be feasible for smaller utilities.

Finally, another area of great interest in smart grids is the ability of artificial intelligence and machine learning models to provide explanations for why they made a particular decision. While many models are now able to provide some explanation as to why they chose one option over another, most models currently being used are "black box" models, i.e., they provide no indication as to why they chose a particular course of action. Utility managers want to know that they can understand exactly why an artificial intelligence system chose a particular course of action. Therefore, researchers are working on developing explainable artificial intelligence (XAI).

In addition to the four issues listed above, there are two additional concerns in the development of intelligent early warning systems for smart grids. First, smart grids are vulnerable to cyber-attacks, whether through hackers attempting to gain unauthorized access into the grid's computer systems or through maliciously inserting false information into the grid's data streams. Second, smart grids store sensitive customer information and therefore require robust data privacy measures to ensure that customer information remains confidential.

Many researchers believe that developing advanced intelligent early warning systems that can handle all of the previously mentioned problems simultaneously will lead to improved climate resilience for the electric grid. These systems could include a combination of quantum computing and artificial intelligence and edge intelligence and federated learning and digital twin technology and block chain security.

7. CONCLUSION

This report provided an in-depth look at weather hazards for protecting resilient power systems with Early Warning Systems (EWS). Traditional weather forecast methodologies were reviewed along with Machine Learning and Deep Learning and Hybrid Intelligent Models. A review of the literature was completed to show how severe weather like flooding, cyclones, lightning storms, heat waves, wildfires, large amounts of rain or snow have adverse effects on both the reliability and stability of electric power distribution grids. A comparison of the analytical results from the two types of predictive methodologies indicated that AI based forecasting methodologies are more accurate, allow for adaptation during the learning process, and provide operational intelligence when compared to conventional statistical methodology. Other machine learning algorithms such as Random Forest, XGBoost, CNN, LSTM, BILSTM, ConvLSTM and their hybrids performed well in predicting the occurrence of weather-related hazards and potential outages.

However, there is still much work to be done to overcome some significant barriers to the use of AI-based forecasting methodologies. These include high computational costs and lack of transparency regarding how the predictions are being made, lack of robust cybersecurity measures to protect against cyber-attacks on the networked systems of the smart grid; limited availability of real-time data; and limited ability to integrate multiple simultaneous hazards into one model. In addition to these limitations, there has been limited research focused on addressing the need for an integrated climate risk assessment approach; development of scalable low cost solutions for developing countries; and developing and validating transparently adaptive AI systems.

In order to address these limitations, this report developed a quantum LSTM-based intelligent multi-hazard early warning system (IWEWS) using AI, IoT sensors and applications, cloud computing, satellite imagery and geospatial information systems (GIS), and quantum deep learning for real-time hazard detection and adaptive protective control of the smart grid. The IWEWS provides support for intelligent decision making, preventive maintenance of equipment and sub-systems within the grid, mitigation of outages caused by hazardous conditions; and provides support for operating resiliently through all levels of climate variability.

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